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Some Determinants of the Price of Default Risk

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Some Determinants of the Price of Default Risk*

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Abstract

In this paper we study the pricing of credit risk as reflected in the market for credit default swaps (CDS) between 2003 and 2008. This market has newly emerged as the reference for credit risk pricing because of its use of standardized contract specifications and has achieved a higher level of liquidity than typically prevails in the markets for the underlying notes and bonds of the named corporate issuers.

We initiate our exploration by studying a particular case which allows us to set out some of the issues of CDS pricing in a simple way. We show that for the purposes of accounting for relatively short-term changes of CDS spreads, an approach based on the structural (or firm-value based) models of credit risk faces an important obstacle in that reliable information about the firm's liabilities required to calculate the "distance to default" are available only quarterly or in some cases annually. Thus structural models account for short-term movements in credit spreads largely by changes in the issuer's equity price. In the case studied we show the effect of equity returns in explaining weekly changes of spreads is insignificant and of the wrong sign. In examination of particular episodes when the CDS spread was particularly delinked from the firm's equity series, we find that a likely explanation is *changes in expectations* about the firm's planned capital market operations. Since these are hard to capture in an observed proxy variable, we argued that this motivates the use of *latent variable* models that have recently been employed in the credit risk literature. We further see that movements in the CDS spreads for the particlar name chosen are highly correlated with an *index* of CDS spreads for industrial Blue-chip names.

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* *Preliminary and incomplete. Please do not circulate. Comments welcome*

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Building on these observations we then consider CDS pricing for a panel of firms for which CDS contracts were traded between between September 2003 and through January 2008. To facilitate comparison we have drawn our sample from two sectors, energy and media, from North America and Europe. Overall we have 41 firms across four subsamples allowing us to make two-way comparisons (across sectors and regions). Our estimates of a linear model show a strong positive association between spread changes on individual names and a broad-based index of CDS price changes. In contrast, the association with equity prices is very weak, generally statistically insignificant, and often of the wrong sign. These results are robust to inclusion of firm fixed or random effects. We find a negative autocorrelation of residuals in these panel estimates which we interpret as evidence of mean reversion in unobserved risk factors. All these results are consistent across our four subsets, i.e., they hold for North American Energy and Media and European Energy and Media.

We pursue our study by exploring a latent variable model recently introduced in the literature which assumes that defaults on a name follow a jump process where the log intensity of arrivals of defaults itself follows an Ornstein-Uhlenbeck process. After developing a continuous time model of CDS pricing with this underlying stochastic process, we estimate our model for our 41 firms individually, applying no restrictions across firms. Our results are rather mixed in the sense that some firms do seem have mean reverting default intensities and others do not. Overall the evidence of mean reversion is stronger in our study than that found previously.

The estimated models are then used to produce an implied time-series of instantaneous default intensities for our 41 firms observed at weekly intervals. We carry out a principal components analysis of the panels of default intensities for our four sector-region combinations. In all cases a very high fraction of weekly variations in the implied default intensity is explained by a single common factor. We find that the implied common factor for each subsample is highly correlated with the default intensity implied by the index of CDS spreads on Blue-chip names. This is strong evidence confirming the presence of a general credit risk factor whose existence has been proposed in a number of recent contributions.

We then ask what our estimates of default intensities derived from CDS prices imply for the market price of default risk. In order to answer this question we need to compare our estimates of the *risk neutral* intensity process with estimates of the *statistical default* process. We argue that recent studies which have used the Moodys-KMV EDF (estimated default frequencies) are essentially confounding information about the risk-neutral and statistical default distributions. Other estimates based on ratings suffer from the well-know problem of inertia in ratings changes. We therefore employ proxies for the statistical default intensities derived from a large panel data set of North American firms using firm accounting variables as well as macro covariates. Specifically, we use the estimates recently derived by Zhou (2007) who employs a methodology similar to Shumway (2001) and Campbell *et al* (2005) but corrects for possible sample selection bias induced by the earlier studies' treatment of missing observations. These estimates are implemented for our North American firms only. Our results show that in both the energy and media subsamples risk-neutral intensities are much more variable than statistical intensities. A high proportion of observed variation in both kinds of intensities is accounted for by firm level differences. There is a high positive correlation between risk neutral and statistical default intensities.

We then combine estimates to find the implied market price of risk measured as the natural logarithm of the ratio of risk-neutral intensity and statistical intensity of default. We show that a relatively high fraction of the observed variation of this market price of default risk can be accounted for by a common time variation. In order to identify this factor, we explore a linear model of the market price of default risk using as observed covariates macro indicators, firm indicators and indicators of equity market and credit market conditions. Our estimates show a strong association between that credit market conditions and the market price of risk. The estimated coefficients have the correct signs. These are robust findings across a variety of alternative proxies for credit market conditions and across our two subsamples. In contrast equity market risk factors and general business conditions do not always have coefficient estimates of the right sign and are not always significant. However, there is some evidence that changes in the value firm premium are partially correlated with changes in the pricing of default risk. Overall, our results provide evidence of the partial segmentation of credit markets.

Some Determinants of the Price of Default Risk

1 Introduction

The rise of the credit derivatives market has meant that we now can observe rather directly how the market views the price of bearing default risk. In particular, single name credit default swaps (CDS's) provide the credit protection buyer insurance against default by a borrower in that in the event of default by the named firm the CDS buyer will receive par in return for delivering to the CDS seller a bond or note issued by the defaulting firm. The net value of this exchange is the loss given default (LGD) on the delivered security. Prior to default the credit protection buyer pays a periodic premium to the credit protection seller. This CDS spread is determined in a well-developed OTC market that has attracted an increasing number of participants who regularly stand ready to buy or sell CDS's on a wide variety of names for standard terms of 1, 3, 5 years and often longer. Thus the CDS spread is the market's view of the fair price for bearing the risk that the underlying name will default within period covered.[1]

This forward looking way of evaluating credit risk can be contrasted with the traditional credit markets practice of evaluating the risk of default by reference to the historical experience on defaults by comparable firms. The most wide-spread approach uses ratings-based models that associate credit risk with the frequency with which firms within a given ratings category have defaulted over a particular historical period.[2] Alternatively, historical data on default (or bankruptcy) experience have been used to estimate default risk with duration based models.[3] These models have been used to identify firm specific and macroeconomic factors that appear to explain past variations in default frequency and can be used to predict the risk of future defaults.

Conceptually when we estimate default probabilities based on historical default experience we are estimating the *physical* default distribution that should give the actuarially fair value of default risk. In contrast, CDS spreads can be used to infer the *risk neutral* default distribution.[4] The difference between the physical distribution and and risk neutral distribution will reflect the market's premium required for bearing the associated risk.

[1]A basic reference on the theory of valuing default swaps is Duffie and Singleton. The development of the credit derivatives market is documented in the British Banker Association Survey of Credit Derivatives. Further discussion of the market can be found in Duffie (BIS 2007) and Anderson and McKay (2008)

[2]*Credit Metrics* is a well known model used by practitioners. See Crouhy *et.al.* for an introduction to ratings based credit risk models.

[3]See Shumway (2001), Campbell and Hilscher (2005), and Duffie, Saita, and Wang (2005).

[4]More specifically the default distribution reflects both the probability of default (PD) and the loss given default (LGD).

A number of recent studies of the CDS prices have attempted to identify the market price of default risk in this manner and have found that the price appears to be surprisingly high given that it would appear possible to diversify much of default risk by holding a portfolio of claims on a wide variety of names. It was also seen that the price of default risk bearing appears to vary substantially over time and that it seems to have fallen considerably between 2002 and 2004. (See Driessen, Berndt *et al*, and Saita).[5]

In this paper we revisit this question of the behavior of the market price of default risk. One difference with previous studies is that we use a different data set on CDS prices which includes information through early 2008 a period which includes the disruption of the credit markets brought on by the collapse of the market for sub-prime mortgages. Second, in constructing our measure of the market price of default risk we employ a hazard based estimate of physical default intensity which potentially avoids pitfalls encountered in earlier studies. Finally, and most important, we explore directly time series properties of the estimated market price of credit risk using in a model with covariates controlling for firm specific effects and general business conditions. We consider whether it might be accounted for by the partial segmentation of credit markets from the rest of financial markets along the lines suggested by Berndt *et al.*

2 Case Study: Pioneer Natural Resource Co.

In this section we introduce some of the basics of default swap analysis through the study of a particular case. We consider Pioneer Natural Resource Co., an oil and gas exploration and production company with \$6.3 billion in assets in 2006 and listed on the NYSE.

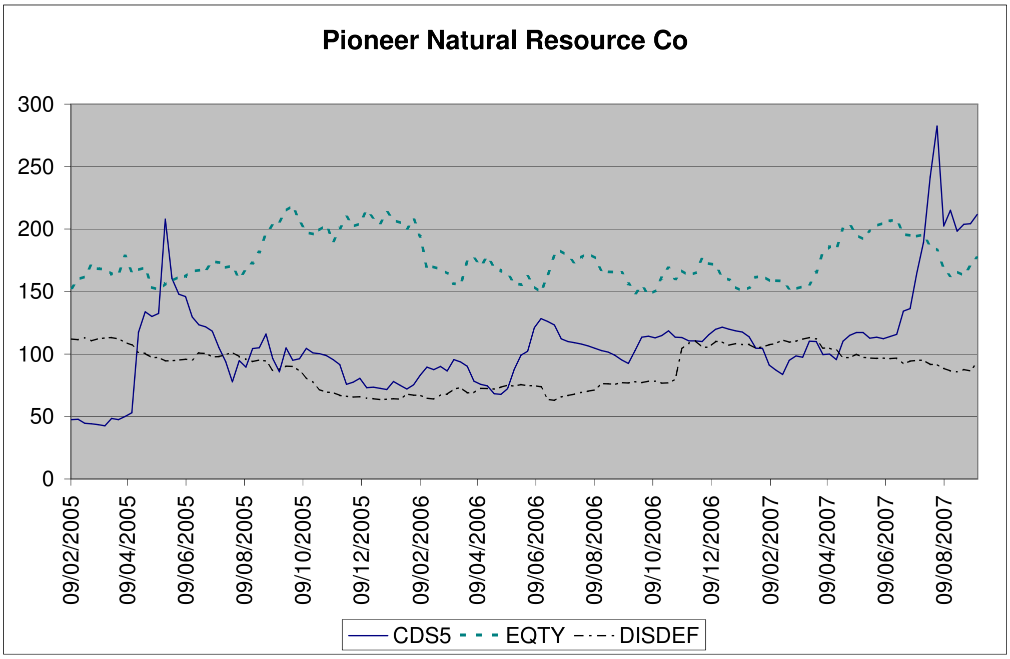
Figure 1 depicts the relation between Pioneer's share price and 5-year CDS spread over the period February 2005 through September 2007. We can observe that the simple correlation of the CDS spread and the equity price is quite low (0.0744). On the assumption that debt outstanding is relatively constant increases in stock value would indicate increases in asset value, a decline in the probability of default and a decrease in CDS spreads. This simple logic is what is implicit in many implementations of structural models of credit risk and also in the use of distance to default as in commercial practice. However, it is not what we often see operating in the in the case of Pioneer. If we regress the log weekly changes of the Pioneer CDS and on the log weekly changes of its equity we obtain, $dln(PICDS) = 0.002 + 0.25 dln(PIEQTY)$ with an R-squared of 0.0078. The slope of this regression is

[5]Some earlier literature studied the price of default risk using data on corporate bonds. Conceptually the spread between corporate bonds and comparable default risk free bonds should be equal to the CDS spread in the absence of arbitrage. In reality observed corporate bond spreads may differ from CDS spreads and give a somewhat distorted assessment of default risk for a variety of important institutional reasons including tax effects, illiquidity of corporate bond markets, call features, coupon effects, and specialness of benchmark Treasury issues among others.

positive rather than the negative relation conventionally expected, and it is statistically insignificant.

Figure 1: Pioneer 5-Year CDS, Equity and Distance to Default

This figure plots charts the time path of Pioneer Natural Resource Co. five-year CDS, equity price and distance to default observed weekly on Wednesdays between February 2, 2005 and August 29, 2007.



As an example of the weak linkage between credit and equity markets consider the diagram in 2005 between March 16 and May 25. Over this period Pioneer's 5-year CDS rose from 42.5 bps to 160.5 bps. During the same period the share price declined slightly from \$42.28 to \$38.68. The background to these changes was that in 2004-2005 Pioneer was scaling back its explorations and production plans and was projected to generate substantial free cash flow. The company announced that it was to undertake a program of debt reduction and share buy-backs. The situation was complicated by the fact that Pioneer had recently engaged in two "volumetric production payments" (VPP's) generating cash proceeds of \$943 million.[6]. By themselves these VPP's could be viewed an

[6]VPP's are forward sales of mineral rights which leaves the seller with risk over production costs

increase in debt. However, the proceeds were to be used for a combination of debt reduction and share buy-backs, the scale of which was uncertain at the time. This led analysts to view the capital market operations as negative on balance for creditors. In this context the CDS spread spiked up and stood at more than 70 bps in excess of firms in the sector with the same BBB- rating. Subsequently, when the uncertainties about Pioneer's capital market operations were removed, the CDS spread fell back in line with comparable firms.[7]

Note that in this period, what seemed to be an important factor driving CDS prices was the *expectation* about *future* capital market operations of the firm. Over the same period, the actual amount of Pioneer's observed leverage moved very little. This can be seen in Figure 1 where we have plotted "distance to default" as well. This latter measure is a standard way that a company's liabilities are often captured in the analysis of credit risk. It is calculated as the difference between the value of the firm's assets and the firm's bankruptcy barrier expressed expressed in multiples of the volatility of the firm's assets. This measure is motivated by Merton's 1974 analysis of debt pricing and has been popularized in the commercial world by Moodys-KMV which uses it in the calculation of its expected default frequencies (EDF's) for listed firms. From Figure 1 we see that the distance to default for Pioneer does not seem to track Pioneer's CDS spread very well. The regression of changes in its CDS spread on changes in distance to default yields, $dln(PICDS) = 0.0104 - 0.3227dln(PIEDISDEF)$ with an R-squared of 0.0106. Now the slope is of the correct sign, but it is insignificant.

Another period when the CDS market and the equity market for Pioneer moved independently was from late May through mid July 2007. Specifically between May 23 and July 18 the CDS spread rose sharply from 112.7 bps to 189.3 bps, an increase of 70 per cent. Over the same period the Pioneer's share price was almost unchanged, falling from \$49.85 to \$49.28. Unlike the previous example, in this period there was very little news emerging that pertained either to Pioneer's business or its capital market operations.[8] This was however the period when the collapse of the sub-prime mortgage market in the United States was beginning to unsettle the credit markets. This manifested itself in the rise of credit spreads generally as evidenced by the rise of the index for CDS spreads for large US firms from 49.7 bps to 72.4 bps, an increase of 46%. Over this same period, equity markets generally were quiet. The S&P500 index moved from 1531 to 1540. Thus during this period market movements in the Pioneer CDS seemed to be explained by some *common factor* which was affecting credit market *but not* affecting the equity markets either for its own shares or shares generally. This period coincided with discussions in the business press suggesting that there had been a recognition that credit risk generally had been underpriced. In some cases there were suggestions of behavioral explanations of this to the effect that investors had increased their aversion to *credit risk* but not to risk generally.

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[7]This discussion draws upon a Deutsche Bank *Credit Watch Report* from April 26, 2005.

[8]During this period there were no articles on Pioneer appearing in the *Wall Street Journal* and a search of analysts reports of the period reveals nothing very significant in our reading.

Figure 2: Pioneer CDS and Blue Chip CDS Index

This figure plots the time path of an index of 5-year CDS speads for Pioneer and the CDS Index for US firms included in the S&P 100 index.[9] Both are expressed in basis points. The regression of the weekly log changes of the Pioneer CDS on weekly log changes of the Index of CDS spreads yields the equation $dln(PICDS) = 0.0055 + 0.8870dln(CDSINDEX)$ with an R-squared of 0.3496.

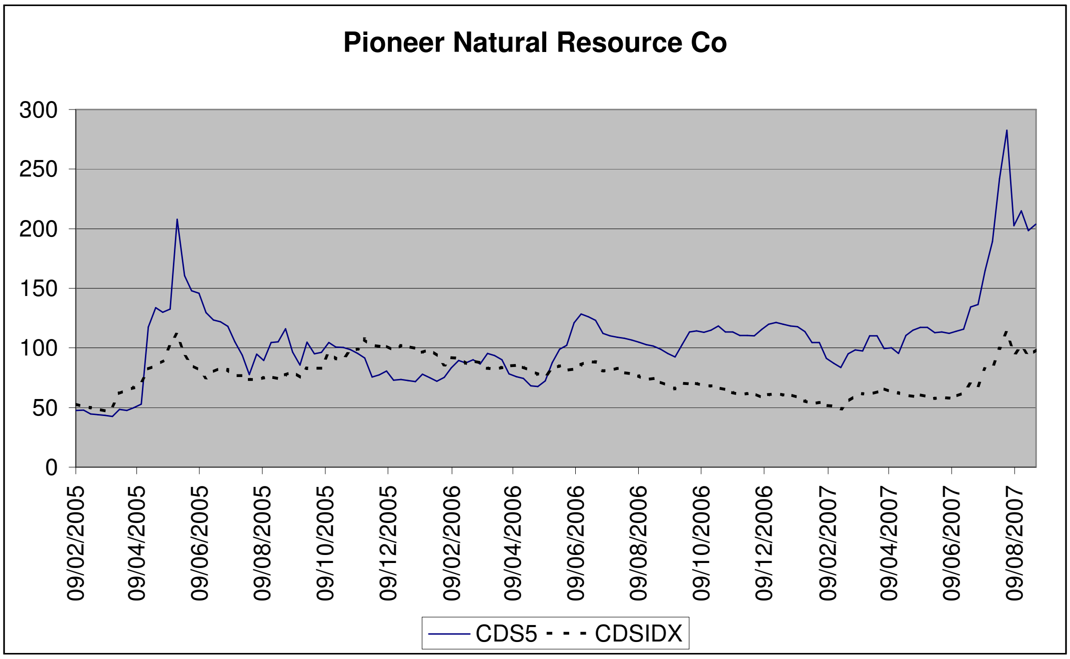


Figure 2 plots the Blue Chip CDS index along with Pioneer's CDS. The two series do seem to move somewhat together. In levels the simple correlation coefficient is 0.33. The simple regression of the log weekly changes in Pioneer's CDS on the log weekly change of the Blue Chip CDS index has a beta of 0.88 and an R-squared of 0.34. This does seem to suggest that allowing for the possibility of a common credit factor may be an important step toward understanding the behavior of single-name CDS's. It is of course possible that Pioneer's credit spreads are influenced by a common factor and also firm specific information captured in its equity price. Table I presents the

[9]Specifically, we selected from firms included in the S&P 100 US equity index those firms which had CDS quotes included in the Datastream data set on single name CDS. After cleaning the data for missing observations, obvious coding errors, and long periods of stale quotes we were left with 62 firms for which 5 year CDS were actively quoted between July 15, 2003 and September 4, 2007. The index is calculated as the simple average of these quotes expressed in basis points.

results of the multilinear regression of log changes of Pioneer's CDS on the log changes of both its equity price and the index of CDS prices. We see that controlling for Pioneer's equity price changes increases the coefficient on the CDS index to 1.15, i.e., the elasticity of Pioneer to the index is about unity. This is very highly significant. Now, controlling for the common movements in the CDS spread, we find the coefficient on changes of Pioneer's equity return is still positive, contrary to what theory would suggest. The effect is small and statistically insignificant.

TABLE I: Pioneer CDS Return

Dependent Variable	dlnPICDS		
Variable	dlnCDSIDX	dlnPIEQTY	constant
Coefficient	1.1562	.0552178	.0055758
p-value	0.000	0.787	0.506
R-squared	0.3500	NOBS	133

3 Statistical Analysis of CDS Pricing

In this section we build on our discussion of the particular case of Pioneer Natural Resource Company to consider the determinants of CDS spreads for a broader sample of firms. The main points we retain from the case studied so far are:

- Among the firm specific variables available equity changes may be expected to be related to changes in CDS spreads.
- CDS spreads may also be associated with a common factor not captured by the issuer's equity prices. We may be able to capture this with an index of CDS prices.
- CDS spreads may be influenced by *expectations* of the issuer's capital market operations such as share buy-backs or debt repayments. These expectations may not be reflected in contemporaneous accounting information.

The first two points were reflected in the multiple regression of CDS returns on equity returns and returns on a CDS index. Thus we first apply this linear model to a panel of firms with actively traded CDS contracts. We then consider whether the influence of expectations might be captured through the introduction of one or more latent variables. In particular, we consider a model introduced by Saita (2006) which assumes a firm-specific intensity of default which drives the pricing of all the firms' CDS issues. We then use the results of this model applied on a firm by firm basis, to construct a panel of default intensities. We consider whether we can identify a *common default intensity*. Finally, we explore whether this common intensity can be associated with observable variables.

TABLE II CDS Prices, Summary Statistics

Firm	Mean CDS Spread	Std Dev of Spread
North American Energy Sector		
ANADARKO PETROLEUM	34.01	7.84
APACHE	23.94	4.43
CHEVRON	11.44	3.73
CONOCOPHILLIPS	22.45	5.48
DEVON ENERGY	36.17	12.52
EXXON MOBIL	7.23	3.19
MARATHON	31.84	8.69
MASSEY ENERGY	255.99	101.69
NEWFIELD EXPLORATION	128.14	49.66
OCCIDENTAL PETROLEUM	26.01	7.20
PEABODY ENERGY	131.69	38.24
PIONEER NATURAL RESOURCES	110.81	46.40
SUNOCO	40.87	8.44
WILLIAMS COMPANIES	161.00	63.26
XTO ENERGY	50.37	23.52
North American Media Sector		
BELO CORP	88.22	36.35
CHARTER COM	897.04	653.47
COMCAST	46.76	18.05
GANNETT	39.32	15.55
INTERPUBLIC	222.68	85.30
OMNICOM	31.39	11.92
TIME WARNER	51.11	16.78
VIACOM	49.96	15.28
WALT DISNEY	31.57	15.75
European Energy Sector		
BP	10.43	11.70
ENI	13.31	12.09
REPSOL	42.99	25.34
SHELL	12.73	11.27
STATOIL	15.15	10.83
TECHNIP	34.98	24.92
TOTAL	13.22	11.29
European Media Sector		
BSKYB	43.27	16.60
PEARSON	45.21	15.36
PROSIEBENSAT	176.96	122.48
PUBLICIS	52.04	27.00
REUTERS	26.55	8.64
SES	45.80	21.30
THOMSON	89.17	88.72
VIVENDI	54.84	21.43
WOLTERS	48.50	17.06
WPP	41.86	25.32

3.1 Data

Our basic data on CDS pricing cover firms with 1, 3 and 5-year CDS contracts quoted on a daily basis on Datastream between September 2003 and through January 2008. To facilitate comparison we have drawn our sample from two sectors, energy and media, from North America and Europe. Overall we have 41 firms across four subsamples allowing us to make two-way comparisons (across sectors and regions). For North American firms we have taken CDS contracts denominated in US dollars. For European firms the contracts are quoted in euros or pounds sterling. The firms included in our study as well as the mean and standard deviation of the 5-year CDS spread are listed in Table II.

It will be observed that our data set spans quite a wide range of firms with mean spreads going from a minimum of 7.23 basis points for EXXON-MOBIL to 897 basis points for CHARTER COMMUNICATIONS. Broadly speaking spreads are higher for media firms than energy firms. And spreads are higher for North American firms than European firms.

We also use indices of spreads on large firms as in our discussion of the Pioneer case. For North America we have constructed an index of Blue Chip CDS spreads from individual quotes for firms included in the Standard and Poors 500 equity index which had 5-year CDS's quotes available on Datastream for the period September 2003 through end of August 2007. In all 62 firms were included. The CDS index was calculated as the arithmetic average of the quoted spreads. Among the 15 energy companies the only ExxonMobil was also included in the calculation of the CDS index. For European Firms we use a chained series from constructed from iTraxx 5-year, on-the-run spreads.

3.2 Linear Regressions

In this section we apply the regression model introduced in our case study of a single firm to balanced panels for the four sets of firm we cover. In particular, we consider the model,

$$\Delta lnCDS_{it}^{5} = \alpha_i + \beta \Delta lnS_{i,t} + \gamma \Delta lnIndxCDS_t^5 \tag{1}$$

where for firm i, $\Delta lnCDS_{i,t}^{5}$ is the weekly change of the logarithm of the spread on firm's 5-CDS, $\Delta lnS_{i,t}$ is the corresponding log change of the firm's equity price and $\Delta lnIndxCDS_t^5$ is the log change of the index of CDS quotes. We implement this model for the four subsamples separately. The results are reported in Table III.

TABLE III Linear Model Estimates:
Dependent Variable, Weekly Change of log of CDS spread
(p-values in parentheses)

North American Energy Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	-.1135	-.1129	-.1135	-.1163	-.1186
	(0.084)	(0.087)	(0.084)	(0.093)	(0.085)
$\Delta lnIndxCDS5_t$	.6930	.6931	.6930	.6945	.6943
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	-.0002	-.0002	-.0002	-.0001	-.0001
	(0.875)	(0.875)	(0.875)	(0.944)	(0.935)
ρ				-.2738	-.2738
R-squared	0.0416	0.0416	0.0416	0.0416	0.0416
Number of obs	3120	3120	3120	3120	3120
North American Media Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	.0168	0.0200	0.0168	0.0318	0.0278
	(0.832)	(0.802)	(0.832)	(0.692)	(0.727)
$\Delta lnIndxCDS5_t$	0.846	0.8470	.8465	0.8503	0.8468
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	.00012	0.0001	.0001	0.0001	0.0001
	(0.925)	(0.925)	(0.925)	(0.965)	(0.926)
ρ				-.098	-.0938
R-squared	0.1124	0.1124	0.1124	0.1124	0.1124
Number of obs	2052	2052	2052	2052	2052
European Energy Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	-0.0425	-0.0416	-0.0425	-0.0598	-0.0613
	(0.654)	(0.662)	(0.654)	(0.541)	(0.530)
$\Delta lnIndxCDS5_t$	0.5463	0.5463	0.5463	0.4977	0.4994
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.0028	0.0028	0.0028	0.0022	0.0029
	(0.049)	(0.049)	(0.049)	(0.135)	(0.114)
ρ				-0.187	-0.187
R-squared	0.2428	0.2428	0.2428	0.2428	0.2428
Number of obs	931	931	931	931	931
European Media Sector Variable	Pooled	Fixed Effect	Random Effect	FE AR(1)	RE AR(1)
$\Delta lnS_{i,t}$	-0.2961	-0.2896	-0.2961	-0.3058	-0.3090
	(.0014)	(0.000)	(0.000)	(0.000)	(0.530)
$\Delta lnIndxCDS5_t$	0.5659	0.5667	0.5659	0.5528	0.5521
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.0014	0.0014	0.0014	0.0012	0.0014
	(0.087)	(0.088)	(0.087)	(0.131)	(0.114)
ρ				-0.0965	-0.0966
R-squared	0.3786	0.3786	0.3786	0.3786	0.3786
Number of obs	1680	1680	1680	1680	1680

The results for the pooled least squares regression ($\alpha_i = \alpha$ for all i) for North American energy firms are given in the first column of Table III top panel. These result are quite similar to those obtained for the firm Pioneer Natural Resources separately. That is, the movements of the firm's CDS spreads are negatively related to changes in the firm's equity price as theory predicts; however, the relation is weak and only marginally statistically significant. In contrast, the energy firm's CDS spreads are strongly related to an index of CDS spreads for very large liquid firms drawn from all industries. And this common factor is highly statistically significant.

Also for North American energy firms columns 2 and 3 of Table III report results for the same linear model using panel data methods for firm groups. The results using either fixed effects or random effects are virtually the same as those obtained in the pooled regressions. Columns 4 and 5 give results of panel methods allowing for first order serial correlation of errors. The coefficient estimates of the regressors are very similar to those obtained previously. It is noted however that the autocorrelation coefficient of the errors is -0.27 which is suggestive of some mean reversion of unobserved factors.

The results in the other three panels largely replicate these findings. In all cases the coefficient on the log change of the index of CDS spreads is positive and highly significant. The estimated autocorrelation of residuals is negative suggesting some mean reversion. For North American media and European Energy the coefficient on the return on the firms equity is insignificant. The only slight surprise is that for European media firms this coefficient is significant and negative. This suggests some hope that traditional structural models of credit risk might find some scope for application in that sector.

4 The Market Implied Default Intensity

4.1 A Latent Variable Model of CDS Pricing

As discussed in section 2, it is likely that not all the systematic determinants of CDS prices can be readily represented with empirically observed proxy variables. For this reason we wish to explore models that capture unobserved risk factors as latent variables. In credit risk modelling the most widely used class of models of this sort are reduced form models which treat the default event as a continuous time stochastic process.[10] In particular, following Saita and Berndt et.al. we assume that the default for a given name i arrives with a default intensity that is independent of the instantaneous risk-free rate. We indicate this intensity at time t under the risk-neutral process as $\lambda_i^Q(t)$. Then at time t the probability p_{it}^T that firm i will not default prior to some date T in the future is given by,

$$p_{it}^T = E^Q[e^{-\int_t^T \lambda_i^Q(s)ds}] \tag{2}$$

Thus for example, the value d_{it}^T at time t of a promise by firm i to pay \$1 at time T assuming loss given default of 100% is, $d_{it}^T = e^{-r(T-t)}p_{it}^T$ where r is assumed to be the constant risk-free rate.

[10] See Duffie and Singleton chapter 5 for an introduction to reduced from models and chapter 8 for their application to CDS pricing.

There is no firmly established empirical evidence on the behavior of latent default risk factor $\lambda_i^Q(t)$. The regression results of the previous subsection gave some evidence of mean reversion. This is consistent with the stochastic process adopted by Saita, namely that the log of the default intensity follows an Ornstein-Uhlenbeck process.[11] Setting $X_t^i = ln\lambda_i^Q(s)$, we assume,

$$dX_t^i = k_q^i(\theta_q^i - X_t^i)dt + \sigma^i dZ_t^{iq}, \tag{3}$$

where dZ_t^{iq} is a Brownian motion under the risk-neutral process.

4.2 Estimation

We will estimate the parameters of the risk-neutral process k_q^i, θ_q^i and σ^i from observations of the spreads of CDS's written on firm i. The estimating equation can be developed from CDS pricing relations as follows. Under the CDS the protection seller will receive a periodic payment of C at regular intervals until date T in the future or until default if this occurs prior to T. From date t suppose there are n payment dates $t(j)$ until $T = t(n)$. Then the value of the cash flows to the protection seller are, $C\Sigma_j^n d_{it}^{t(j)}$. The protection buyer will receive compensation for the loss of value on a bond issued by firm i incurred at default at some stochastic time τ in the future. Let the loss given default (LGD) be given as a random amount L that will be paid at the time of default.[12] Thus the value of cash flows to the protection buyer is $E_t^Q e^{-r(\tau-t)}L$. The fair value of the CDS spread at any given time is the C which just equates the value of cash flows of the protection seller and the protection buyer. That is, it satisfies,

$$C\Sigma_j^n d_{it}^{t(j)} = E_t^Q e^{-r(\tau-t)}L \tag{4}$$

Let the spread that solves this pricing equation be written as $f(t, T, k_q^i, \theta_q^i, \sigma^i, \lambda_q^i(t))$. Note that in this expression we explicitly take into account that at time t all expectations are conditional upon the current value of the default intensity $\lambda_q^i(t)$.

The parameters k_q^i, θ_q^i, and σ^i are estimated assuming that observed quotes on CDS spreads deviate from theoretical spreads by an additive normal error. Specifically for firm i we obtain a panel of observations on 1, 3 and 5-year CDS at discrete times $t = 1, M$. Let these quoted spreads be indicated as CDS_{it}^T for $T \in 1, 3, 5$. Then our statistical model is,

$$\begin{aligned} CDS_{it}^T = f(t, T, k_q^i, \theta_q^i, \sigma^i, \lambda_q^i(t)) + u_{it}^T \\ T \in 1, 3, 5 \\ t = 1, M \end{aligned} \tag{5}$$

[11]Berndt *et al* p.24 also adopt the O-U process as part of a somewhat more complicated specification for the log default intensity.

[12]In practice it is often assumed that promised payment to the protection buyer is a constant percentage of the face value of the claim. However, even in this case the payment to the protection buyer will be stochastic since it will need to be adjusted by deducting any accrued spread due at the time of default which is stochastic.

We estimate this model using an iterative simulated quasi-maximum likelihood procedure very similar to that employed by Saita. Specifically, each iteration proceeds as follows:

1. *Given* values of the parameters k_q^i, θ_q^i, and σ^i we obtain a time series of implied default intensities $\lambda_q^i(t)$ by solving equation (5) for $T = 5$ assuming assuming $u_{it}^5 = 0$ for $t = 1, M$.

2. *Given* the time series $\lambda_q^i(t)$ for $t = 1, M$ choose k_q^i, θ_q^i, to minimize the sum of squared residuals $\Sigma_{T\in 1,3}\Sigma_{t=1}^{M}[CDS_{it}^T - f(t, T, k_q^i, \theta_q^i, \sigma^i, \lambda_q^i(t))]^2$.

The procedure is continued until convergence is obtained. The assumption that the theoretical model prices the 5-year CDS exactly is admittedly a bit arbitrary, but it is in line with market practice where the 5-year issue is often the most liquid, benchmark issue. Notice that a by-product of the procedure is an estimate of the time series of instantaneous default intensities, $\lambda_q^i(t)$ for $t = 1, M$. Implementation of this procedure is carried out by numerical integration to calculate the expectations in equation(4) and by simulating a discretized version of equation (3). More details on the appropriate numerical procedures are provided in Saita and in Berndt *et al.*

This procedure was applied to the 41 firms listed in Table II. Samples consisted of weekly observations between September 2003 and January 2008. Note that the method was applied for each firm separately with no restrictions imposed across equations. In principle, it might be interesting to explore cross-equation restrictions on the parameters; however, in practice this would be difficult. Indeed, given the large number of Monte Carlo simulations involved in each separate function evaluation, the computations of estimates for the 41 firms considered here were carried out over two months. So imposing cross equation restrictions on parameters to be estimated would require simultaneous estimation is probably infeasible.

The parameter estimates obtained for the four subsamples of firms are listed in Table IV.

TABLE IV Latent Variable Parameter Estimates, Energy Sector

Firm	σ^i	k^i_q	θ^i_q
North American Energy Sector			
ANADARKO PETROLEUM	1.109	0.0097	-5.9739
APACHE	1.6821	0.3255	-6.461
CHEVRON	1.3694	0.1686	-7.9679
CONOCOPHILLIPS	0.6277	0.3089	-4.8142
DEVON ENERGY	0.8925	0.3297	-4.9476
EXXON MOBIL	0.8226	0.0159	-6.6214
MARATHON	0.6479	0.3625	-4.5898
MASSEY ENERGY	0.813	-0.1178	-4.7534
NEWFIELD EXPLORATION	0.2433	-0.041	-7.0053
OCCIDENTAL PETROLEUM	1.3633	0.0522	-8.01
PEABODY ENERGY	0.8944	0.0141	-7.1023
PIONEER NATURAL RESOURCES	0.8253	-0.0343	-7.9969
SUNOCO	0.1411	0.3336	-4.0925
WILLIAMS COMPANIES	1.2005	0.1675	-5.1114
XTO ENERGY	0.5289	0.4461	-4.3722
North American Media Sector			
BELO CORP	0.7838	-0.0229	-5.9746
CHARTER CO	0.8740	-0.1012	-4.8567
COMCAST	0.3011	0.0949	-2.1992
GANNETT	0.6544	0.2185	-3.9947
INTERPUBLIC	0.7010	-0.0752	-4.1653
OMNICOM	0.1517	0.2431	-3.9796
TIME WARNER	0.4063	0.1112	-2.5059
VIACOM	0.0299	-1.8518	-5.4096
WALT DISNEY	0.3552	0.2753	-4.1559
European Energy Sector			
BP	1.0367	0.0022	-6.0163
ENI	0.7736	0.0572	-6.0545
REPSOL	0.5993	0.2042	-3.7571
SHELL	0.9754	-0.0055	-6.0310
STATOIL	0.7885	0.1261	-6.0473
TECHNIP	0.9321	-0.0437	-5.9977
TOTAL	0.9379	0.0953	-6.0554
European Media Sector			
BSKYB	0.9422	0.0258	-9.6959
PEARSON	1.1919	0.1363	-5.4009
PROSIEBENSAT	0.8501	-0.2388	-4.3114
PUBLICIS	0.5584	0.2406	-3.5949
REUTERS	0.4710	0.2509	-4.4194
SES	1.2564	-0.2433	-4.1582
VIVENDI	0.7387	0.2619	-4.3320
WOLTERS	1.0647	0.0474	-6.0107
WPP	0.3678	0.1276	-2.4437

From these results we see that for most firms the estimated value of the parameter k^i_q is positive and for about half the firms it exceeds 0.1 suggesting CDS contracts are priced on the assumption of strong mean reversion in the default intensity process. However, for quite a few of the firms the estimated mean reversion parameter is close to zero or is negative. For these firms the O-U specification may not be appropriate. To explore this matter further, we graphed the likelihood surface in k_q^i X θ_q^i and confirmed for several of the firms the likelihood function was extremely flat in the neighborhood of $k_q^i = 0$. Thus for these firms, we cannot reject the hypothesis of that the log default intensity follows a random walk. Note these comments pertain to the *risk neutral* process and do not speak to the issue of mean reversion in statistical default intensities. Overall, our estimates of the mean reversion parameter were rather higher than those reported by Saita Table 2 and Appendix A. In contrast, the volatility of the intensity process, σ^i was rather precisely estimated and the ranged between 0.029 and 1.86 which was in line with the estimated reported by Saita.[13]

4.3 Time Series Behavior of Market Implied Default Intensity

Perhaps of even greater interest than the parameter estimates are the estimates of the time-series of the default intensities, $ln\lambda_{it}^Q$, implied by the estimated model. We are particularly interested in whether these estimates for the 41 firms estimated independently may exhibit any common patterns. To do so we carried out a principal components analysis for the four subsamples of firms. The results of these analyses can be seen in Table V where we report the proportion of the variation explained by the first five principal components.

TABLE V Principal Component Analysis of Implied Default Intensities

Component	1	2	3	4	5
North American Energy Sector					
Variance explained, marginal	0.6852	0.1156	0.0580	0.0402	0.0264
Variance explained, cumulative	0.6852	0.8008	0.8588	0.8990	0.9254
North American Media Sector					
Variance explained, marginal	0.7428	0.1828	0.0266	0.0215	0.0127
Variance explained, cumulative	0.7428	0.9255	0.9521	0.9736	0.9863
European Energy Sector					
Variance explained, marginal	0.9352	0.0209	0.0176	0.0109	0.0082
Variance explained, cumulative	0.9352	0.9561	0.9737	0.9846	0.9928
European Media Sector					
Variance explained, marginal	0.7039	0.1526	0.0657	0.0301	0.0168
Variance explained, cumulative	0.7039	0.8565	0.9222	0.9523	0.9691

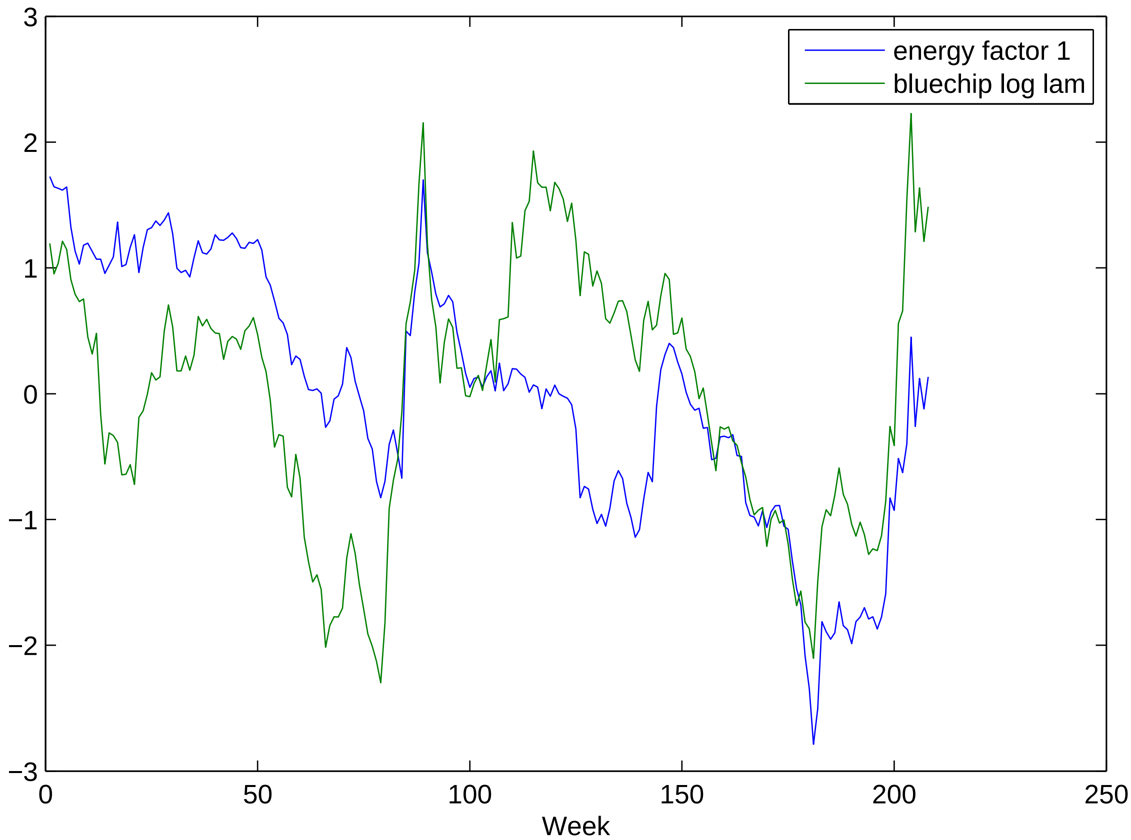
From this we see that a large fraction, ranging from 68% to 93%, of the time series variation of the instantaneous default intensities implied by the the first principal component of calculated

[13]Our sample covers different names than those used by Saita. Furthermore, he included observations taken between June 1998 and June 2004 which overlapped with our sample for less than one year.

for weekly observations between September 2003 through January 2008. This is strong evidence of a common determinant of price of credit risk within each of the four subsamples. Now this factor could reflect determinants that are specific to that sector, or it may reflect more general determinants of the market price of credit risk. To investigate this further we compare the implied time series of the latent factor implied by the first principal component of default intensities in the energy sector with the default intensity implied by the index of CDS spreads. The results for the North American Energy Sector are summarized in Figure 4.

Figure 4: Energy Common Factor and Blue Chip CDS Factor

This figure plots the log intensities implied by the CDS Index for US firms included in the S&P 100 index and the common factor implied by the first principal component of the log intensities of the fifteen energy companies over the 208 weeks from 10/9/03 through 29/8/07. For visual comparability, both series have been normalized by subtracting the sample mean and dividing by the sample standard deviation. The correlation of the two series is 0.47.



The correlation between the common energy default factor and the default factor for the Blue-chip factor is quite high (47%). In the figure it is striking the many of the extreme moves in one series are very precisely mirrored in the other series. At other times, the two series appear to be poorly correlated. This pattern suggests that there may be both a broad-based credit risk factor that influencing credit markets generally as well as a sectoral factor that may be specific to the energy industry. What seems remarkable here is that the dominant common factor that emerges from the *unsystematic* components identified in the default intensities for fifteen energy firms estimated *independently* should emerge so clearly as closely linked to the central tendency of default risk captured in the default swaps of 62 firms of which 61 do not overlap with our energy sample.

A similar pattern holds for the other subsamples. The first principle component in the estimated log intensities of our independently estimated model accounts for a very high proportion of the total variation of these intensities. Furthermore, the underlying factor reflected in this component is highly correlated with the general index of CDS spreads. For the four subsamples the correlations between the first factor as above and the index of CDS spread (SPIdxCDS for North America and iTraxx5 for Europe) are:

Sample	N.Am. Energy	N.Am Media	Eu.Energy	Eu.Media
Correlation	-0.444	-0.5582	-0.9137	-0.9036

To summarize, we have estimated a latent variable model for CDS pricing for 41 firms in four distinct sectors and covering a wide range of credit quality. We have estimated the models independently and have explored the extent to which the estimated implied risk-neutral default intensities follow some common tendency. We find that in each sector studied a common factor accounts for a large proportion of the variation of the implied default intensity. Furthermore, this common factor is highly correlated with movements of a general index of CDS prices. Now this common factor could reflect co-movements in the statistical probability of default. Or it could reflect time variation in a common market price of default risk. We attempt to explore this issue in the next section.

5 The Market Price of Default Risk

5.1 The Relation of Market Implied and Historical Default Intensities

The market price of default risk reflects the discount on a defaultable security in addition to that which is justified by the statistical default process. An advantage of the reduced form model that we have adopted here is that this price of default risk has a natural interpretation as the ratio of the intensity of default under the risk neutral process and the intensity from the statistical distribution. Thus to identify the market price of default risk we will combine our estimates of the intensity of default derived from CDS prices with estimates that have been derived from historically observed instances of default or bankruptcy.

There have been several recent attempts to estimate statistical default process from historical episodes of financial distress.[14]. In comparing those studies with estimates of the risk neutral process such as those given above it is important to emphasize differences in the two estimation problems. *First*, the most important point is that financial distress is a rare event. That is, most firms whose securities are traded in the market have never defaulted and have never experienced financial distress. Thus, inevitably to obtain estimates of the probability of financial distress we will need to work with large *cross sections* of firms including both those that have experienced distress and those that have not. *Second*, in dealing with large cross-sections of firms it will be necessary to control firm characteristics which are reflected in their financial reports which are available on a quarterly or annual basis. Thus in capturing time variations of the physical intensity of default we will work at a much higher level of temporal aggregation than we do when estimating risk neutral default processes from market quotes. *Third*, in working with panel data with financial ratios as covariates there may be significant problem of missing observations. This is particularly true for firm experiencing financial distress where early stages of distress may involve difficulty in producing audited financial statements. For this reason, estimates of the physical default process potentially may be prone to sample selection bias.

Our estimates of the physical distress process for our sample of firms are derived from Zhou (2007) who employs a methodology similar to Shumway (2001) and Campbell *et al* (2005) but corrects for possible sample selection bias induced by the earlier studies' treatment of missing observations. In particular, working with quarterly observations for North American firms between 1995 and 2005 she documents the fact that important accounting variables frequently missing from the data set. Given that missing accounting variables may be associated with the on-set of financial distress, a method based on simply deleting firm/quarters with some missing explanatory variables, as in Campbell *et al* is potentially exposed to self-selection bias. Zhou shows that the estimates of the model are sensitive to the method adopted in treating missing observations and argues that the method of multiple imputations is best equipped to correct for this problem.

Following this methodology our estimate of the physical default intensity can be written as:

$$\lambda^P = e^{4(X'\hat{\beta})} \tag{6}$$

where X is a vector of regressors entering into the hazard function estimation and $\hat{\beta}$ is the associated vector of parameter estimates. Note that in this expression we multiply the coefficient estimates by 4 to express Zhou's quarterly estimates as an intensity per year. Using the results in her Table 14, this can be expressed as:

$$\begin{aligned} ln(\lambda^P) = 4 * (&-9.3022 - 10.3148NITA + 4.8065TLTA \\ &-1.3812PRICE - 0.2514EXRET + 1.8190SIGMA) \end{aligned} \tag{7}$$

The definition of variables in this equation are given in Table VI which describes our quarterly data set including those variables used in the regression analyses reported below.

[14]See Shumway (2001), Campbell *et al* (2005) and Duffie *et al* (2005)

TABLE VI Quarterly Data Descriptions

Variable	Description	Source
$ln(\lambda^Q)$	log intensity of default in risk neutral distribution	Own calculations
$ln(\lambda^P)$	log intensity of default in physical distribution	Zhou (2007), own calculations
NITA	net income over total assets	Compustat
TLTA	total liabilities over total assets	Compustat
PRICE	log of min(share price, $15)	Datastream
EXRET	log excess monthly return on share over S&P500	Datastream
SIGMA	standard deviation of daily stock returns in past three months	Datastream
GDPGTH	growth rate of GDP	US Dept of Commerce
OILPRICE	West Texas intermediate	FRED, St.Louis Fed
RETSP	Return on S&P 500 composite index	CRSP
NPCMCM2	Nonperforming Com. Loans Banks w/ Assets from $300M to $1B	FRED, St.Louis Fed
NPCMCM5	Nonperforming Com. Loans Banks with Total Assets over $20B	FRED, St.Louis Fed
NPTLTL	Nonperforming Total Loans	FRED, St.Louis Fed
USROE	Return on Average Equity for all U.S. Banks	FRED, St.Louis Fed
FRBSURVEY	Percent Tightening Standards for Commercial Loans	Fed Senior Loan Officer Opinion Survey
MKTRF	Market return in excess of risk free	Ken French Data Library
SMB	Small-minus-big (small firm premium)	Ken French Data Library
HML	High-minus-low (value firm premium)	Ken French Data Library
RF	Three month Treasure rate	Ken French Data Library

It should be noted that the measure of financial distress employed by Zhou and Campbell *et al* is either bankruptcy or the assignment of a 'D' rating. This may a stricter definition than that which applies in the documentation for a given firm's default swap. As a consequence, the estimate of the physical default intensity may be systematically below that would have obtained had a broader default definition been adopted. For example, if conditional on triggering a CDS credit event, the probability of bankruptcy is a constant 0.5, then the physical credit event intensity will be approximately twice the the corresponding physical bankruptcy intensity. For this reason, in our discussion below of our calculated ratios of risk neutral to physical default intensities, λ^Q/λ^P, we confine our attention to the factors that may account for the *variations* of this ratio in our sample, as opposed to making statements about the magnitude of the ratio.[15]

Our use of the estimates based on a quarterly panel of *firm-specific* and other variables can be contrasted with two alternative approaches to identifying the physical default process that can be

[15] The *level* of the intensity ratio is the central question investigated by Saita who fails to find an explanation for high levels obtained in his estimates.

found in the recent literature. In his study of corporate bond prices in the 1990's, Driessen (2005) uses estimates of the physical default process that are based on Moody's and S&P's historical estimates of average default rates and matches them to firm level data by the bond rating. Given the well-documented inertia in ratings, this approach is problematic since changes in firm condition observed by the market but not reflected in a ratings change could lead the analyst to conclude that an explanatory factor affects the risk premium when in fact it affected the physical default intensity. A very different approach has been adopted by Berndt *et al* (2005) who take as the estimate of the physical default probability the EDF "expected default frequency" on a given name that is distributed commercially by MOODYS-KMV. Now EDF's are estimated by KMV as a monotone function of the firm's "distance to default". As we have seen in our discussion of the Pioneer case above, given infrequent updating of information on liabilities, most of the intertemporal variation in in distance to default will be derived from movements in stock prices. As a consequence, changes in EDF's will be a composite reflection of information about the firm's future prospects and the market price of risk bearing in equity markets. Thus, EDF's will confound estimates of the physical and the risk neutral default processes.

Given the important differences in accounting conventions in Europe and North America and given that the estimates of Zhou have been based on a sample of North American firms, we also confine our analysis to our North American firms. Our sample of 15 North American energy firms spans sixteen quarters from Q1 2003 through Q4 2006; our sample of 9 North American media firms covers fifteen quarters from Q2 2003 through Q4 2006. Our quarterly estimates of the risk neutral intensities of default were derived from our estimates reported in Table IV. Specifically, we have calculated the quarterly averages of the weekly default intensities implied by those estimates.

Some important characteristics of the resulting estimates of the physical and risk neutral default intensities can be seen from a two-way analysis of variance allowing for quarter and firm effects. These are reported in Table VII. Our results show that in both the energy and media subsamples risk-neutral intensities are much more variable than statistical intensities. This is particularly noticeable for the energy subsample where the total sum of squared deviations of the risk neutral intensities exceed that of the physical intensities by a factor of 3. This is perhaps not surprising since the energy subsample consists of relatively highly rated firms where the pure credit component of spreads may be relatively low.

A high proportion of observed variation in both kinds of intensities is accounted for by firm level differences. There is a high positive correlation between risk neutral and statistical default intensities. We would expect this, but it is still an important result. Given that the two types of intensities were derived independently and using very different methodologies, the positive correlation encourages us in believing that the quarterly, *backward-looking* physical default model is capturing influences perceived as important by the market *on a forward-looking basis.*

Given this result, we then calculate the estimated implied market price of default risk as the natural log of the ratio of risk neutral and physical default intensities. A two-way ANOVA of these estimates is also reported in Table VII. Again firm effects account for a high proportion of total variation. However, we see the time effect is also quite important, accounting for 16% and 21% of total variation in the energy and media subsamples respectively. In the next section we will try to explore factors that may account for this time variation in the market price of credit risk.

TABLE VII Two-way ANOVA of Physical and Risk Neutral Intensities

Sample Dependent variable	*N.American Energy* $ln(\lambda^P)$	*N.American Energy* $ln(\lambda^Q)$	*N.American Energy* $ln(\lambda^Q/\lambda^P)$	*N.American Media* $ln(\lambda^P)$	*N.American Media* $ln(\lambda^Q)$	*N.American Media* $ln(\lambda^Q/\lambda^P)$
Number of obs	233	233	233	119	119	119
R-squared	0.8726	0.9095	0.7920	0.8873	0.8114	0.7362
Model SS	124.27	441.99	215.47	73.97	136.65	85.48
Firm SS	121.91	396.96	176.22	71.01	106.26	63.49
Time SS	4.31	62.92	43.59	2.24	26.74	23.97
Residual SS	18.14	43.977	56.59	9.39	31.75	30.62
Total SS	142.42	485.96	272.06	83.36	168.40	116.11
Correlation	0.6791			0.5725		

5.2 Determinants of the Market Price of Default Risk

In this section we explore whether the variation in the market price of default risk that we have identified may be accounted for by observable factors either specific to the firm or general factors reflecting business conditions. In particular, we wish to explore whether specific indicators of credit market conditions appear to account some of observed variation and whether any such influence is robust to including general financial market conditions. Such a finding would be evidence in support of a possible segmentation of credit markets from other financial markets as has been conjectured by Berndt *et al.*

TABLE VIII Panel A:
Linear model estimates of the market price of credit risk
N.American Energy(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	233	233	233	233	233	233
R-SQ(within)	0.3335	0.3354	0.3112	0.2938	0.2818	0.2497
NITA	3.794	3.774	3.863	4.050	3.297	4.081
	0.122	0.125	0.122	0.109	0.197	0.117
GDPGTH	-17.298	-20.549	-12.216	-.421	-19.462	-2.902
	0.057	0.039	0.183	0.965	0.042	0.777
OILPRICE	.012	.013	.0109	.004	-.027	-.020
	0.058	0.053	0.127	0.506	0.000	0.000
RETSP		-4.505				
		0.419				
NPCMCM2	2.462	2.551				
	0.000	0.000				
NPCMCM5			.553			
			0.000			
NPTLTL				1.877		
				0.000		
USROE					.674	
					0.000	
FRBSURVEY						.008
						0.012
CONSTANT	-3.061	-3.111	-1.270	-2.049	-6.586	1.044
	0.000	0.000	0.016	0.007	0.001	0.000

The variables used for external factors in are summarized in Table VI. In addition to standard macroeconomic and firm accounting variables we include information on the condition in the chief suppliers of credit as represented by the banking sector. These are derived from two principles sources. The first set of variables come from the Federal Reserve System's "Reports of Condition and Income for All Insured U.S. Commercial Banks" and available on the website of the the St. Louis Fed. The second source of credit condition information is the Fed's "Senior Loan Officer Opinion Survey on Lending Practices". We use these data in estimating linear models applied to the default risk premium of our North American Energy and Media firms as estimated above. As suggested by the analysis of variance results reported in Table VI, we include firm fixed effects in all of our estimates reported here. We have also estimated the models excluding fixed effects but including more firm financial ratios as controls. The results are qualitatively the same as those we report here.

Our results for North American Energy Firms are reported in Table VIII, Panel A. The first column reports our benchmark model. Earnings (NITA) is included as an indicator of firm specific business conditions. It enters with a positive sign which may be surprising. However, it is insignificant, which suggests that firm specific influences are largely captured in the constant fixed-effect.

GDP growth is included as a general business conditions indicator. It is marginally significant. It is not immediately clear what the direction this influence should be on the market price of default risk. The negative sign obtained here might be suggestive of a "credit cycle" as commonly discussed among practitioners. The oil price is included and may serve both as a control for general business conditions and as a sector-specific indicator relevant to the energy sector as a whole. It enters with a positive sign and is marginally significant.

In this benchmark regression a measure of non-performing commercial loans is included as an indicator of credit market tightness. Its role in the credit channel is clear– increases in non-performing loans will lead to increases in loan loss provisions and typically a reduction of regulatory capital ratios. This credit variable, NPCMC2, enters the regression with a positive sign, as we would expect if there is a credit supply effect on the market price of default risk, and it is highly significant.

Column 2 in Table VIII Panel A reports the result of including an index of stock market returns as a control for changes the market price of equity. This variable enters with a negative sign as we would expect, but it not significant. The inclusion of this control variable has no effect on the qualitative effects of the other variables in the regression. In particular, the credit supply variable remains very highly significant and has the correct sign. In the remaining regressions we omit the stock return variable, but the results are robust to its inclusion.

In the remaining columns of Table VIII Panel A we experiment with alternative proxies of credit market tightness. In column 3 we include NPCMCM5 which is a measure of non-performing commercial loans in very large banks (in contrast with NPCMCM2 which is a measure of non-performing loans in relatively small banks). This variable enters with the expected positive sign. It is highly significant, albeit at a somewhat lower level than NPCMCM2 as can be seen from the R-squared. This might suggest that performance of loan portfolios of small, less diversified, banks may more informative than the loan portfolios of large banks. In column 4, non-performing loans for the banking system as whole is our proxy for credit market tightness. Again it enters with the expected sign and is significant. Column 5 uses average return on equity in the banking sector as the credit supply proxy, and this has the correct sign and is significant. Finally, in Column 6, we use the Fed's lending officers' survey variable as a credit sector indicator. It enters with the expected positive sign and is significant.

The general point that emerges from these regressions is that credit market tightness appears to be a significant determinant of the market price of credit risk after controlling for firm specific effects, general business conditions, and equity market conditions. This conclusion does not depend greatly on the precise way in which credit market tightness is measured. However, we have found that the best single proxy appears to be an indicator of non-performing loans at smaller commercial banks. The effects of non-credit variables in the regression are largely robust to the choice of the credit tightness proxy used. The sole exception is the oil price variable which sometimes enters with a positive sign and sometimes with a negative sign.

TABLE VIII Panel B:
Linear model estimates of the market price of credit risk
N.American Media(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	118	118	118	118	118	118
R-SQ(within)	0.2523	0.2756	0.2111	0.1830	0.1423	0.1367
NITA	6.537	6.655	5.485	5.238	5.311	5.356
	0.216	0.203	0.311	0.342	0.347	0.345
GDPGTH	1.730	-8.656	11.058	24.050	17.320	20.959
	0.902	0.564	0.432	0.093	0.236	0.167
OILPRICE	.027	.029	.020	.011	-.005	-.014
	0.013	0.009	0.079	0.298	0.587	0.001
RETSP		-15.565				
		0.060				
NPCMCM2	3.214	3.506				
	0.000	0.000				
NPCMCM5			.622			
			0.001			
NPTLTL				1.998		
				0.012		
USROE					.187	
					0.343	
FRBSURVEY						.002
						0.673
CONSTANT	-4.799	-4.976	-2.109	-2.797	-2.648	.430
	0.000	0.000	0.014	0.035	0.421	0.219

The results for this framework applied to the North American media sector are reported in Table VIII Panel B. Again, firm fixed effects are included. The contrast with North American energy firms is interesting because of exposure of the sectors to different economic conditions (i.e., greater exposure to commodities and business cycle in the energy sector) and because media firm are typically less highly rated with higher CDS spreads on average. The results in the table show that indeed these differences do appear to be manifested in the way the market price of credit risk is determined in the media sector. The GDP growth variable is generally insignificant as we might expect for a sector less exposed to business cycle influences. However, the oil price variable enters significantly in most specifications although not always with the same sign. Also, the return on the equity index now is marginally significant.

However, the main result for the North American media firms is the same as for energy firms. The most important explanatory variable for the market price of default risk is the proxy for credit market tightness. Again the best proxy appears to be the index of non-performing loans in smaller commercial banks. But similar results are obtained using non-performing loans in large banks. Overall, the evidence for the two sectors suggest that credit market conditions are important determinants of the market price of default risk even after taking into account firm specific effects, general business conditions and equity market conditions.

Of course, in this analysis of the market price of default risk there is a wide variety of alternative variables that could be tried. We have explored some of these possibilities including such firm measures as leverage or equity volatility and general business conditions measures such as industrial production, other commodity prices and the University of Michigan index of consumer sentiment. Two conclusions emerge from all these explorations. First, none of these additional control variables turns up as significant across both subsamples and across the various alternative specifications. Second, credit market tightness proxies remain consistently significant and of the right sign across these alternative specifications.

The results in Table VIII suggest that after controlling for firm level and sectoral differences a significant part of the time variation in the market price of default risk is accounted for by time variation in credit market tightness. This is consistent with the idea that the market for default risk may be segmented from other financial markets as has been conjectured by Berndt *et al.* We pursue this idea by augmenting our benchmark model to include the Fama-French risk factors that have been widely used in the analysis of equity markets. Specifically, we use the quarterly average of the monthly data reported on Ken French's Data Library (as described in Table VI).

The results for the North American energy sector are presented in Table IX, Panel A. The first three columns show the result of introducing individually each of the three Fama-French factors into our benchmark model. The excess return on the market and the small firm premium are both insignificant; however, the HML variable enters with a negative sign which is highly significant. This suggests that controlling for other factors, periods of relatively high returns on value stocks are associated with low market prices of default risk. Column 4 reports results with the short-term Treasury rate included. It enters with a negative sign but is insignificant. When the three Fama-French factors are included jointly (column 5), HML again enters with a significant negative sign and the two others are insignificant. Interestingly, when both HML and the risk free rate are included (column 6) both are negative and significant.

Thus we find evidence that the factors that appear as significant risk factors in equity markets do account for some of the common time variation of the market price of default risk. However, a striking finding in Table IX, Panel A is that the estimated coefficients of the credit market tightness variable (NPCMCM2) are almost identical across all specifications and are very highly significant. This suggests that while equity market conditions do seem to some impact credit markets, specific credit supply factors remain highly important in accounting for the time variation in default risk pricing.

TABLE IX Panel A:
Equity market risk factors
N.American Energy(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	233	233	233	233	233	233
R-SQ(within)	0.3410	0.3336	0.3534	0.3401	0.3624	0.3680
NITA	3.705	3.801	3.049	3.807	2.910	2.901
	0.130	0.123	0.211	0.120	0.232	0.230
GDPGTH	-20.229	-16.794	-15.042	-23.919	-15.535	-24.757
	0.029	0.092	0.095	0.018	0.249	.013
OILPRICE	.008	.0123	.011	.0243	.006	.029
	0.251	0.053	0.087	0.018	0.360	0.005
NPCMCM2	2.284	2.462	2.241	2.578	2.054	2.370
	0.000	0.000	0.000	0.000	0.000	0.000
MKTRF	-.038				-.0338	
	0.110				0.360	
SMB		-.004			-.0149	
		0.900			0.791	
HML			-.0961		-.106	-.117
			0.009		0.020	0.002
RF				-1.205		-1.860
				0.135		0.023
CONSTANT	-2.567	-3.055	-2.710	-3.418	-2.215	-3.184
	0.002	0.000	0.000	0.000	0.009	0.000

Table IX, Panel B reports the results for North American Media Firms. The results for the equity risk factors are very similar to those for the energy firms. Movements in the value premium do seem to be partially correlated with movements in the market price of default risk while equity market premium and the small firm premium are not. Again, when the risk free rate is include along with the HML variable, both are negative and significant. As with the energy firms, the effect of the credit market tightness variable is rather insensitive to the inclusion of the equity market risk factors– its coefficient is negative and highly significant in all cases.

TABLE IX Panel B:
Equity market risk factors
N.American Media(p-values below coefficient estimates)

Dependent variable $ln(\lambda^Q/\lambda^P)$						
Number of obs	118	118	118	118	118	118
R-SQ(within)	0.2526	0.2527	0.2842	0.3020	0.2909	0.3646
NITA	6.688	6.417	5.498	8.006	5.912	6.967
	0.211	0.229	0.291	0.121	0.262	0.160
GDPGTH	.423	.181	-.776	-18.977	.328	-29.304
	0.978	0.991	0.955	0.223	0.989	0.056
OILPRICE	.0274	.028	.030	.060	.029	.075
	0.016	0.013	0.005	0.000	0.010	0.000
NPCMCM2	3.230	3.220	3.362	3.658	3.409	4.017
	0.000	0.000	0.000	0.000	0.000	0.000
MKTRF	-.009				-.018	
	0.816				0.781	
SMB		.011			-.032	
		0.804			0.711	
HML			-.127		-.156	-.186
			0.027		0.022	0.001
RF				-3.185		-4.212
				0.006		0.000
CONSTANT	-4.764	-4.819	-4.964	-5.930	-4.875	-6.535
	0.000	0.000	0.000	0.000	0.000	0.000

To summarize, a large fraction of the variation in the market price of default risk is accounted for by constant firm effects; however, there is significant common time variation. After controlling for macroeconomic and sectoral factors, we find changes in credit market tightness, measured with a variety of empirical proxies, is a significant explanatory variable that is robust to the inclusion of a wide variety of other variables. Beyond this we find that changes in the value premium in equity markets appear to account for some of the variation of the price of default risk.

6 Conclusion

In this paper we study the pricing of credit risk as reflected in the market for credit default swaps (CDS) between 2003 and 2008. This market has newly emerged as the reference for credit risk pricing because of its use of standardized contract specifications and has achieved a higher level of liquidity than typically prevails in the markets for the underlying notes and bonds of the named corporate issuers.

We initiate our exploration by studying a particular case which allows us to set out some of the issues of CDS pricing in a simple way. We show that for the purposes of accounting for relatively short-term changes of CDS spreads, an approach based on the structural (or firm-value based) models of credit risk faces an important obstacle in that reliable information about the firm's liabilities required to calculate the "distance to default" are available only quarterly or in some cases annually. Thus structural models account for short-term movements in credit spreads largely by changes in the issuer's equity price. In the case studied we show the effect of equity returns in explaining weekly changes of spreads is insignificant and of the wrong sign. In examination of particular episodes when the CDS spread was particularly delinked from the firm's equity series, we find that a likely explanation is *changes in expectations* about the firm's planned capital market operations. Since these are hard to capture in an observed proxy variable, we argued that this motivates the use of *latent variable* models that have recently been employed in the credit risk literature. We further see that movements in the CDS spreads for the particlar name chosen are highly correlated with an *index* of CDS spreads for industrial Blue-chip names.

Building on these observations we then consider CDS pricing for a panel of firms for which CDS contracts were traded between between September 2003 and through January 2008. To facilitate comparison we have drawn our sample from two sectors, energy and media, from North America and Europe. Overall we have 41 firms across four subsamples allowing us to make two-way comparisons (across sectors and regions). Our estimates of a linear model show a strong positive association between spread changes on individual names and a broad-based index of CDS price changes. In contrast, the association with equity prices is very weak, generally statistically insignificant, and often of the wrong sign. These results are robust to inclusion of firm fixed or random effects. We find a negative autocorrelation of residuals in these panel estimates which we interpret as evidence of mean reversion in unobserved risk factors. All these results are consistent across our four subsets, i.e., they hold for North American Energy and Media and European Energy and Media.

We pursue our study by exploring a latent variable model recently introduced in the literature which assumes that defaults on a name follow a jump process where the log intensity of arrivals of defaults itself follows an Ornstein-Uhlenbeck process. After developing a continuous time model of CDS pricing with this underlying stochastic process, we estimate our model for our 41 firms individually, applying no restrictions across firms. Our results are rather mixed in the sense that some firms do seem have mean reverting default intensities and others do not. Overall the evidence of mean reversion is stronger in our study than that found previously.

The estimated models are then used to produce an implied time-series of instantaneous default intensities for our 41 firms observed at weekly intervals. We carry out a principal components analysis of the panels of default intensities for our four sector-region combinations. In all cases a very high fraction of weekly variations in the implied default intensity is explained by a single common factor. We find that the implied common factor for each subsample is highly correlated with the default intensity implied by the index of CDS spreads on Blue-chip names. This is strong evidence confirming the presence of a general credit risk factor whose existence has been proposed in a number of recent contributions.

We then ask what our estimates of default intensities derived from CDS prices imply for the market price of default risk. In order to answer this question we need to compare our estimates of the *risk neutral* intensity process with estimates of the *statistical default* process. We argue that recent studies which have used the Moodys-KMV EDF (estimated default frequencies) are essentially confounding information about the risk-neutral and statistical default distributions.

Other estimates based on ratings suffer from the well-know problem of inertia in ratings changes. We therefore employ proxies for the statistical default intensities derived from a large panel data set of North American firms using firm accounting variables as well as macro covariates. Specifically, we use the estimates recently derived by Zhou (2007) who employs a methodology similar to Shumway (2001) and Campbell *et al* (2005) but corrects for possible sample selection bias induced by the earlier studies' treatment of missing observations. These estimates are implemented for our North American firms only. Our results show that in both the energy and media subsamples risk-neutral intensities are much more variable than statistical intensities. A high proportion of observed variation in both kinds of intensities is accounted for by firm level differences. There is a high positive correlation between risk neutral and statistical default intensities.

We then combine estimates to find the implied market price of risk measured as the natural logarithm of the ratio of risk-neutral intensity and statistical intensity of default. We show that a relatively high fraction of the observed variation of this market price of default risk can be accounted for by a common time variation. In order to identify this factor, we explore a linear model of the market price of default risk using as observed covariates macro indicators, firm indicators and indicators of equity market and credit market conditions. Our estimates show a strong association between that credit market conditions and the market price of risk. The estimated coefficients have the correct signs. These are robust findings across a variety of alternative proxies for credit market conditions and across our two subsamples. In contrast equity market conditions and general business conditions do not always have coefficient estimates of the right sign and are not always significant. However, there is some evidence that changes in the value firm premium are partially correlated with changes in the pricing of default risk. Overall, our results provide evidence of the partial segmentation of credit markets.

7 References

Anderson, R. W. and K. McKay, 2008, "Derivatives Markets" in X.Freixas, P.Hartmann, and C.Mayer (eds.), *European Financial Markets and Institutions.* Oxford University Press.

Berndt, A., R. Douglas, D. Duffie, M. Ferguson, and D. Schranz, 2005, "Measuring Default Risk Premia from Default Swap Rates and EDF's" Stanford University, working paper.

Campbell, J. and Hilscher, J. and Szilagyi, J., 2005, "In Search of Distress Risk", Working paper, Harvard University.

Crouhy, M., D. Galai, and R. Mark, 2001, *Risk Management.* McGraw-Hill.

Driessen, J., 2005, "Is Default Event Risk Priced in Corporate Bonds?" *Review of Financial Studies.* 18, 165-195.

Duffie, D., 2007, "Innovations in Credit Risk Transfer: Implications for Financial Stability" Stanford University, working paper.

Duffie, D. and D. Lando, 2001, "Term Structures of Credit Spreads with Incomplete Accounting Information," *Econometrica* 69, 633-664.

Duffie, D., L. Saita, and K. Wang, 2005, "Multi-Period Corporate Default Prediction With Stochastic Covariates", Working paper, Stanford University.

Duffie, D., and K. Singleton, 2003, *Credit Risk*. Princeton University Press.

Saita, L., 2006, "The Puzzling Price of Corporate Default Risk," Stanford University, working paper.

Shumway, T., 2001, "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," *Journal of Business*.74, 101-124.

Zhou, P., 2007, "Forecasting Bankruptcy and Physical Default Intensity'" manuscript, London School of Economics.